Modeling Rheological Properties Of Oil Well Cement Slurries Using Multiple Regression Analysis And Artificial Neural Networks

Anjuman Shahriar [*1], Moncef Nehdi [2]

Department of Civil and Environmental Engineering, The University of Western Ontario
London, ON, N6A 5B9, Canada
[*1]anjuman.shahriar@gmail.com; [2]mnehdi@uwo.ca.

Abstract

Artificial neural networks (ANN) and multiple regression analysis (MRA) were used to predict the rheological properties of oil well cement slurries. The slurries were prepared using class G oil well cement with a water-cement mass ratio (w/c) of 0.44, and incorporating a new generation polycarboxylate-based high-range water reducing admixture (PCH), polycarboxlate-based mid-range water reducing admixture (PCM), and lignosulphonate-based mid-range water reducing admixture (LSM). The rheological properties were investigated at different temperatures in the range of 23 to 60ºC using an advanced shear-stress/shear-strain controlled rheometer. Experimental data thus obtained were used to develop predictive models based on back-propagation artificial neural networks and multiple regression analysis. It was found that both ANN and MRA depicted good agreement with the experimental data, with ANN achieving more accurate predictions. The developed models could effectively predict the rheological properties of new slurries designed within the range of input parameters of the experimental database with an absolute error of 3.43, 3.17, and 2.82%, in the case of ANN and 4.83, 6.32, and 5.05%, in the case of MRA, for slurries incorporating PCH, PCM, and LSM, respectively. The flow curves developed using ANN and MRA allowed predicting the Bingham parameters (yield stress and plastic viscosity) of the oil well slurries with adequate accuracy.

Keywords

Cement slurry; Oil well; Yield stress; Plastic viscosity; Artificial neural network; Multiple regression analysis.

1. Introduction

The recent oil spill in the Gulf of Mexico and the associated environmental and economic impact has put renewed emphasis on the importance of oil well cementing operations. The rheological properties of oil well cement (OWC) slurries are important in assuring that such slurries can be mixed at the surface and pumped into the well with minimum pressure drop, thereby achieving effective well cementing operation. The rheological properties of OWC slurries depend on various factors including the water-cement ratio (w/c), size and shape of cement grains, chemical composition of the cement and relative distribution of its components at the surface of grains, presence and type of additives, compatibility between cement and chemical admixtures, mixing and testing procedures, time and temperature, etc. The interactions among the above mentioned factors play a vital role in altering the rheological properties of OWC slurries. Moreover, a wide range of bottom-hole pressure and temperature makes the characterization of the rheology of OWC slurries more challenging than that of normal cement paste. Therefore, a clear understanding of this complex behavior is important in order to successfully predict the rheological properties of OWC slurries.

Much work has been conducted over the last few decades to investigate the rheological behaviour of cementitious systems such as cement paste, mortar, grout, slurry and concrete. A number of shear stress-strain rate relationships have been developed for cement slurries. However, there exists no model that explains the interactions among the materials used for preparing such slurries and test conditions such as temperature, shear rate, etc. The power-law, Bingham, and Herschel-Bulkley models are the most commonly used in the well cementing industry [Guillot 2006]. Such models are comprised of empirical expressions derived from the analysis of limited experimental data and/or based on simplifying assumptions [El-Chabib and Nehdi 2005]. Moreover, they do not have true predictive capability outside the experimental domain and/or when different materials are used [El-Chabib et al. 2003], and do not explain the interactions among test parameters.

ANN is a powerful computational tool that allows overcoming the difficulty of assessing the complex and highly nonlinear relationships among model parameters through self-organization, pattern recognition, and functional approximation. ANN simulates the structure and internal functions of the biological brain. Unlike conventional models, ANN does not assume a model structure between input and output variables. It rather generates the model based on the database provided for training the network. An ANN solves problems by creating parallel networks and the training/learning of those networks, rather than by a specific programming scheme based on well-defined rules or assumptions [Bruni et al. 2006].

On the other hand, multiple regression analysis (MRA) is a statistical method to learn about the analytical relationship between several independent or predictor variables (input variables) and a dependent or criterion variable (output variable) [Statsoft 2010]. The relations may be linear or nonlinear, and independent variables may be quantitative or qualitative. MRA explains the effects of a single input variable or multiple variables on the output variable with or without considering the effects of other variables [Cohen et al., 2003].

Temperature has been found to have drastic effects on the rheological behavior of cement slurries. Its effect also depends on the type of cement and admixtures used. Thus, it was argued that it would be difficult to find a general model that can represent the temperature dependency of cement slurry rheology [Guillot 2006]. Ravi and Sutton [1990] developed a correlation to calculate the equilibrium temperature for plastic viscosity and yield stress of Class H cement slurries using a high-pressure, high-temperature rheometer. It was found that both plastic viscosity and yield stress increased with the increase in temperature. However, plastic viscosity reached a constant value beyond the equilibrium temperature, whereas there was no evidence for yield stress to attain a constant value beyond a certain temperature. Using the Bingham plastic model, Ravi and Sutton [1990] developed equations to represent the variation of rheological parameters with temperature where the yield stress and plastic viscosity values were measured at 80°F (27°C) and limited to a maximum temperature, Tmax. Their equations below were developed using cement systems containing specific additives, and are thus dependent on the slurry composition.

$$\mu_p(T) = a + (b \times T) + (0.00325 \times T^2) \quad (1)$$

Where, is in mPa.s and T is in °F; and at 80°F; and at 80°F.

Currently, there is need to create a reliable method for predicting the rheological performance of OWC slurries and relating its composition (admixture type, dosage, etc.) and test conditions (e.g. shear rate, temperature) to the expected rheological properties. In this framework, ANN and MRA have been used in the present study to develop models to predict the shear stress of OWC slurries at a given shear rate, as a function of the temperature and admixture dosage. The ability of the models thus developed to evaluate the sensitivity of rheological properties to the variation of shear rate, admixture dosage, and test temperature was investigated. Hence, a shear stress-shear rate curve for OWC slurries can be predicted at different temperatures prior to fitting the data to conventional rheological models. Consequently, the rheological properties of OWC slurries can be predicted as a function of mixture composition and test conditions for the first time.

2. Experimental Program

2.1 Materials

OWC slurries used in this study were prepared using a high sulphate-resistant API Class G OWC with a specific gravity of 3.14. Deionized distilled water was used for the mixing, and its temperature was maintained at 23±1°C using an isothermal container. Three different chemical admixtures including a new generation polycarboxylate-based high-range water reducing admixture (PCH), polycarboxylate-based mid-range water reducing admixture (PCM) and mid-range lignosulphonate based water reducing admixture (LSM) were used to prepare the OWC slurries with a w/c = 0.44. Their dosages are presented in Table 1.

2.2. Apparatus

The OWC slurries were prepared using a variable speed high-shear blender type mixer with bottom drive blades as per the ANSI/API Recommended Practice 10B-2 [2005]. A high accuracy advanced rheometer (TA instruments AR 2000) (Fig. 1(a)) was used to measure the rheological properties of the slurries. The rheometer is capable of continuous shear rate sweep and stress sweep. The coaxial

concentric cylinder geometry was considered suitable for this study because of the typically low viscosity of OWC slurries.

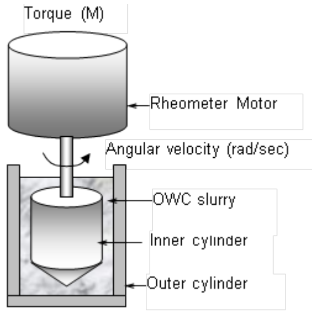
TABLE 1 CHEMICAL ADMIXTURES USED FOR PREPARING OIL WELL CEMENT SLURRIES

Type of admixture	Abbreviation	Dosages % BWOC*
New generation polycarboxylate-based high-range water reducing admixture	PCH	0.25, 0.50, 0.75, and 1.00
Polycarboxylate-based mid-range water reducing admixture	PCM	0.25, 0.50, 0.75, and 1.00
Mid-range lignosulphonate based water reducing admixture	LSM	0.5, 1.0, 1.5 and 2.0

* BWOC: by weight of cement

The geometry consists of a cylinder with a conical end that rotates inside a cylinder with a central fixed hollow as shown in Fig. 1(b). This smooth inner solid cylinder rotates inside a fixed hollow cylinder of 15 mm in diameter. The gap between the head of the conical end and the bottom of the hollow cylinder was set to 0.5 mm for all experiments. It is required to use such a narrow gap in order to main a constant shear rate across the gap, which is important, especially in case of static flow studies to minimize the error caused by wall slip in rheological measurements [Saak et al. 2001]. The rheometer maintains an auto gap in order to compensate for the expansion of the stainless steel of the coaxial concentric cylinders under a wide range of temperatures, thus keeping the gap constant during experiments. The calibration of the rheometer was performed using a certified standard Newtonian oil with a known viscosity of 1.0 Pa.s and yield stress = 0 Pa at 20°C. The measured yield stress was 0 Pa and viscosity was 1.009 Pa.s with an error of 0.9%, which is less than the tolerated error of 4% specified by the manufacturer. The rheometer is equipped with a rheological data analysis software, which can fit the shear stress-strain rate data to several rheological models. The Bingham model was used throughout this study to calculate the rheological properties of cement slurries, i.e. yield stress and plastic viscosity.

(A)



(B)

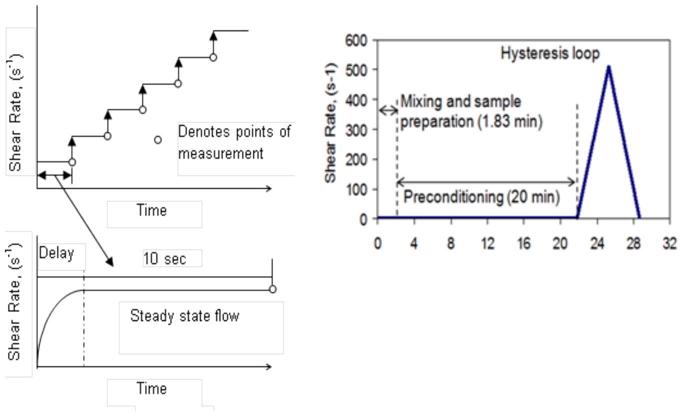
FIG. 1 ILLUSTRATION OF, (A) ADVANCED RHEOMETER WITH COAXIAL CYLINDER GEOMETRY, AND (B) COAXIAL CONCENTRIC CYLINDER WITH CYLINDRICAL CONICAL END GEOMETRY.

3. Experimental Procedure

A high-shear blender type mixer with bottom driven blades was used to prepare the slurry according to the following procedure. First, the weighed amount of cement and solid admixture (if any) were manually dry mixed in a bowl using a spatula for about 30 sec. The mixing water was subsequently poured into the blender. Then the required quantity of liquid admixture was added into the mixing water using a needle. The mixing resumed at slow speed for 15 sec so that chemical admixtures could be thoroughly dispersed in water. The cement was added to the liquids (chemical admixture and water) over a period of 15 sec. Manual mixing was conducted for another 15 sec and a rubber spatula was used to recover any material sticking to the wall of the mixing container to ensure homogeneity. Finally, mixing resumed for another 35 sec at high speed. This mixing procedure was strictly followed for all cement slurries and all mixing was conducted at a controlled ambient room temperature of 23±1°C. The prepared slurry was then placed into the bowl of a mixer for preconditioning (at

150 rpm) over 20 minutes at the specific test temperature (23°C, 45°C, or 60°C). The total time between the beginning of mixing and the start of the rheological tests was kept constant to avoid the effects of exogenous variables on the results. The rheometer set-up was also maintained constant for all tested slurries. The concentric cylinder test geometry was maintained at the test temperature so as to avoid sudden thermal shock of the slurry.

After mixing and preconditioninfg, the cement slurry sample was placed in the coaxial cylinder of the rheometer. The temperature was adjusted to the required level and the sample was then subjected to a stepped ramp or steady state flow where rheological measurements were taken at 20 different shear rates starting from 5.11 s^{-1} up to 511 s^{-1} after a continuous rotation of 10 sec at each level. Subsequently, the data were measured at a descending shear rate from 511 s^{-1} to 5.11 s^{-1} to obtain the down flow curve. A schematic representation of the viscometric testing scheme is illustrated in Fig. 2.



(A) (B)

FIG. 2 (A) SCHEMATIC REPRESENTATION OF STEPPED RAMP, AND (B) RHEOMETER TEST SEQUENCE (SHEAR RATE HISTORY USED IN RHEOLOGICAL TESTS).

4. Experimental Results

Typical shear stress-shear rate down curves of the hysteresis loop for OWC slurries prepared using a new generation polycarboxylate-based high-range water reducing admixture (PCH) at 60°C are presented in Fig. 3. The down-curve better fits the Bingham plastic model than the up-curve [Ferguson and Kemblowski 1991, Al-Martini and Nehdi 2009], therefore the shear rate–shear stress down curve was considered in calculating the rheological properties (yield stress and plastic viscosity) using the Bingham plastic model (equation 2). The rheological parameters thus calculated are highly dependent on the temperature and admixture dosage as can be observed in Figs. 4 and 5.

$$\tau = \tau_0 + \mu_P \bar{\gamma} \tag{2}$$

Where, τ , τ_0 , μ_P , and $\bar{\gamma}$ represent the shear stress, yield stress, plastic viscosity, and shear rate, respectively.

In this study, two different approaches: MRA and ANN have been used to predict the shear stress as a function of test variables (temperature, admixture dosage and shear rate). The predicted flow curve allows in turn predicting the rheological properties of OWC slurries. Hence model predictions and corresponding experimental data can be compared.

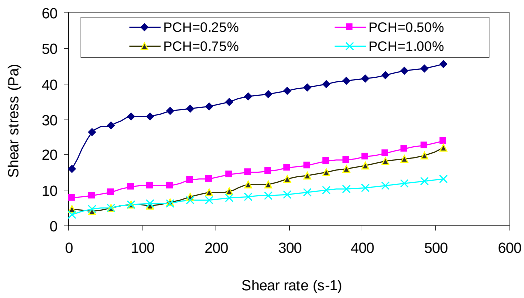


FIG. 3 SHEAR STRESS-SHEAR RATE DOWN CURVE FOR OWC SLURRIES PREPARED USING DIFFERENT DOSAGE OF PCH AT 60°C.

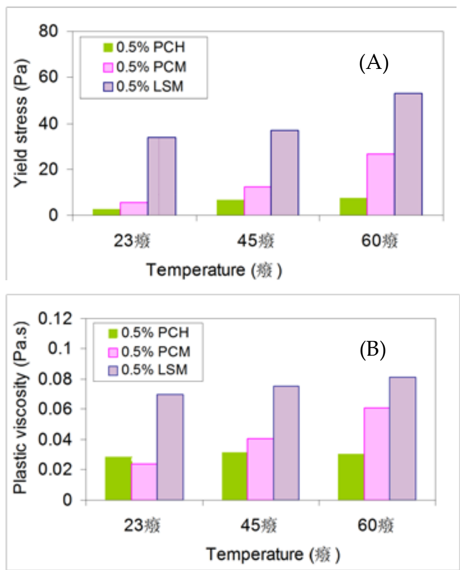
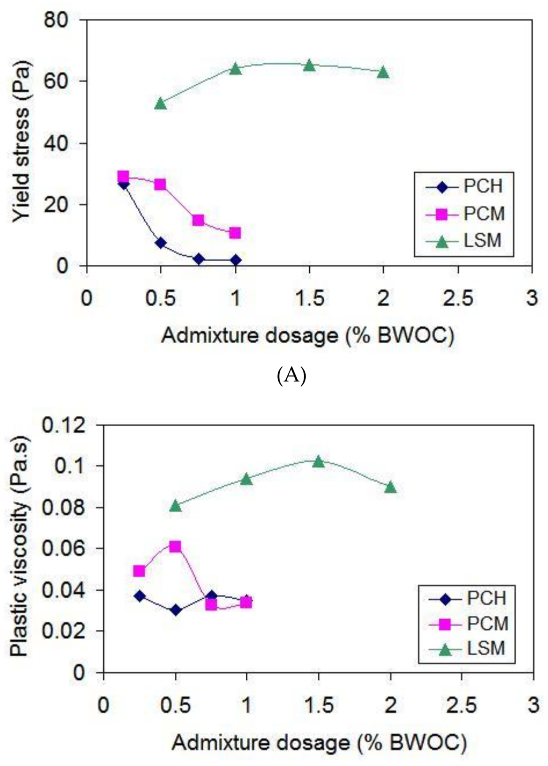


FIG. 4 EFFECT OF TEMPERATURE ON (A) YIELD STRESS, AND (B) LASTIC VISCOSITY OF OWC SLURRY PREPARED USING DIFFERENT ADMIXTURES (0.5% BWOC).

5. Artificial Neural Networks Approach

An ANN is capable of learning the mapping between a set of input data and its corresponding output.

Through training, it becomes capable of predicting output when presented with a new set of data within the practical range of the input used in the training process. The feed-forward back-propagation learning algorithm is the most commonly used in engineering applications, especially in modelling the behaviour of cement based materials. A neural network consists of an input layer, one or more hidden layers, and an output layer of several interconnected linear or nonlinear processing units (neurons). Each processing unit receives multiple inputs from the neurons in the previous layer through the weighted connection, and after performing appropriate computation, transfers its output to other processing units or as a network output using an assigned transfer (activation) function as shown in Fig. 6. In this study, a feed-forward back-propagation neural network was developed to predict the rheological parameters of OWC slurries. The topography and training parameters obtained through trial and error for the ANN model thus developed are presented in Fig. 7 and Table 2, respectively. The model parameters were selected based on the lowest training and testing error. It should be noted that different network architectures can provide satisfactory performance for the same application.



(A)

(B)

FIG. 5 EFFECT OF ADMIXTURE DOSAGE ON (A) YIELD STRESS, AND (B) PLASTIC VISCOSITY OF OWC SLURRY PREPARED USING DIFFERENT ADMIXTURES AT 60°C.

Although ANN have been successfully used in predicting complex nonlinear relationships and in modeling various aspects in cement and concrete research, their efficiency depends on the quality of the database used for training the network architecture, and network training and testing [El-Chabib et al. 2003]. In order to train the model, 570 data points generated in the experimental study described above were used (190 data points for each of the three admixtures tested: PCH, PCM and LSM). Another 150 new data points (50 data points for each of the three admixtures tested: PCH, PCM and LSM) not used in the training, and hence, unfamiliar to the model, but within the range of training data, were used to test the performance of the network. It should be noted that each flow curve consists of 20 data points at equal shear rate intervals starting from 5.11 s^{-1} to 511 s^{-1}.

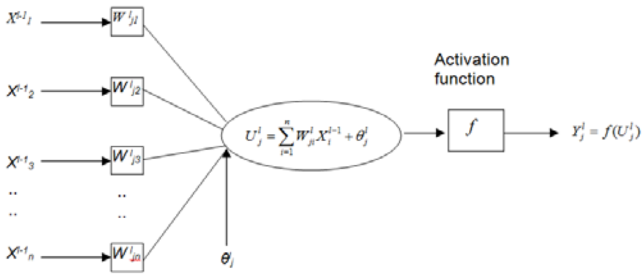


FIG. 6 SIMPLIFIED MODEL OF ARTIFICIAL NEURAL NETWORK

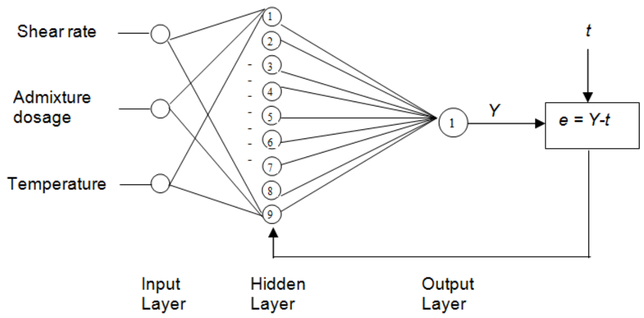


FIG. 7 ARCHITECTURE OF DEVELOPED ANN MODEL.

TABLE 2 TOPOGRAPHY AND TRAINING PARAMETERS FOR THE DEVELOPED ANN MODEL

Number of input nodes	3
Number of output nodes	1
Number of hidden layers	1
Number of nodes in hidden layers	9
Activation function input-hidden layers	Log-sigmoid
Activation function hidden-output layers	Linear
Distribution of weights	Gaussian
Momentum coefficient	0.03
Learning rate	0.05
Convergence	$5E^{-8}$

Specialized commercial computer software [Demuth et al. 2008] was used to train the feed-forward back-propagation neural network in order to predict the

rheological properties of OWC slurries. Supervised training was implemented in this study by providing the network with sets of data (inputs/targets) and the network was instructed what to learn. Parameters such as the learning rate and convergence tolerance used for the ANN are presented in Table 2. A training pattern consists of an input vector of 3 elements including the admixture dosage, temperature and shear rate, and a corresponding output vector consisting of shear stress. The unipolar log-sigmoid (logsig) function and linear function were assigned as the transfer function for the processing units in the input-hidden layers and the hidden-output layers, respectively. Full connection between the processing units in adjacent layers was adopted, whereas no connection was permitted between neurons in the same layer.

After completion of each learning process, the average sum-squared of all errors was calculated and back-propagated through the Levenberg-Marquardt algorithm [Demuth et al. 2008] to adjust the weights or connection strengths between the processing units. This iterative process can continue until the difference between the network prediction and the provided targets is virtually zero. Such over-training, known as over-fitting will not provide acceptable prediction when presented to new mixtures excluded from the training data [El-Chabib et al. 2003]. In order to avoid over-fitting, the iteration was forced to stop early by setting the convergence tolerance or the average sum-squared errors (ASSE) between the training sets and target sets = 5E^{-5}.

6. Multiple Regression Analysis

In the MRA-based approach, the dependent variables yield stress and plastic viscosity were correlated to the independent variables; i.e. shear rate, admixture dosage, and test temperature using first (linear) and then (polynomial) order regression models. It was found that no substantial improvement was achieved by the polynomial regression. Therefore, the linear regression-based approach was used to observe the effect of temperature, admixture dosages and shear rate on shear stress. As a consequence, the shear stress values versus shear rate, admixture dosage and test temperature, were predicted using the following relationship:

$$\tau = a + b\bar{\gamma} + cD_A + dT + e\bar{\gamma}D_A + f\,\bar{\gamma}T + gD_AT + h\bar{\gamma}D_AT \quad (3)$$

where, *a, b, c, d, e, f, g,* and *h* are regression coefficients, and τ, $\bar{\gamma}$, D_A and T are the shear stress, shear rate, dosage of admixture and temperature, respectively.

In order to perform the regression analysis, a total of 240 data points from down curves of the hysteresis loops were used for each of the three admixtures tested (PCH, PCM and LSM). Each data point consists of 3 input variables including shear rate, dosage of admixture and temperature, and one output parameter: shear stress. The least square approach was followed to estimate the coefficients of the model parameters. The interaction between the considered three input parameters and the output parameter were also accounted for during the regression analyses and expressed in terms of t and probability (Prob.>|t|) values. The probability value indicates the probability that the result obtained in a statistical test is due to chance rather than to a true relationship between the parameters [Genentech 2010, Montgomery 2009]. The effects of the input parameters on the output parameters are considered highly significant when t values are high and probability values are low. The parameter is often considered nonzero and significantly influences the response of the model when the probability values are less than 5% [Sonebi 2001, Health and Income Equity 2010].

7. Model Performance

The developed models using the ANN and MRA techniques predicted the shear stress of the OWC slurries and the acceptability/rejection of the model was evaluated using the average absolute error (AAE) given by equation 4 and the correlation coefficient (R2).

$$AAE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|\tau_{measured} - \tau_{predicted}\right|}{\tau_{measured}} \quad (4)$$

where $\tau_{measured}$ and $\tau_{predicted}$ are the experimentally measured shear stress value of OWC slurries and the corresponding data predicted by the model, respectively, and n is the total number of data points.

7.1. Validation of ANN and MRA-Based Models

The artificial neural network model shown in Fig. 7 was trained using 190 training (input/target) pairs for each of the admixtures investigated, and tested using 50 pairs of new data points unfamiliar to the network and not used in the training process.

Figures 8, 9 and 10 illustrate the performance of the ANN in predicting the shear stress of OWC slurries incorporating PCN, PCM, and LSM, respectively. After successful completion of the training process,

the network performance in predicting the shear stress of OWC slurries incorporating PCH was investigated and the results are presented in Fig. 8(a). It can be observed that all data points are located on or in the vicinity of the equity line with an AAE of 3.43%. For cement slurries incorporating PCM, the relationship between measured and predicted shear stress is presented in Fig. 9(a). The model was successfully trained to predict the shear flow with an AAE of 3.17%. Similarly, Fig. 10(a) represents the performance of the ANN model in predicting the shear stress of cement slurries incorporating LSM. It can be observed that the model was able to predict the shear stress of the cement slurries satisfactorily since the measured and corresponding predicted data points are located along the equity line with an AAE of 2.82%.

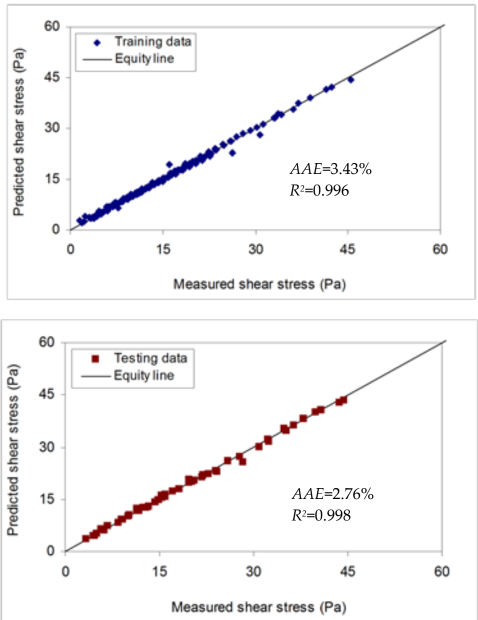


FIG. 8 MEASURED VERSUS ANN-MODEL PREDICTED SHEAR STRESS FOR OWC SLURRIES INCORPORATING PCH.

The acceptance/rejection of the ANN model depends primarily on its performance in predicting the shear stress of new sets of unfamiliar data within the range of input variables of training patterns. In order to validate the developed model, the network was presented with 50 new sets of data which were not used in training the network. In this case, only input vectors of shear rate, dosage of admixture and temperature were presented to the network and no information or knowledge about the corresponding shear stress was provided. The response of the neural network is presented in Figs. 8(b), 9(b) and 10(b) for OWC mixtures made with PCH, PCM and LSM, respectively. The model predictions are accurate since the testing points are located slightly over or under the equity line but within the cluster of training data with an AAE of 2.76, 2.77 and 2.81% for slurries with PCH, PCM and LSM, respectively.

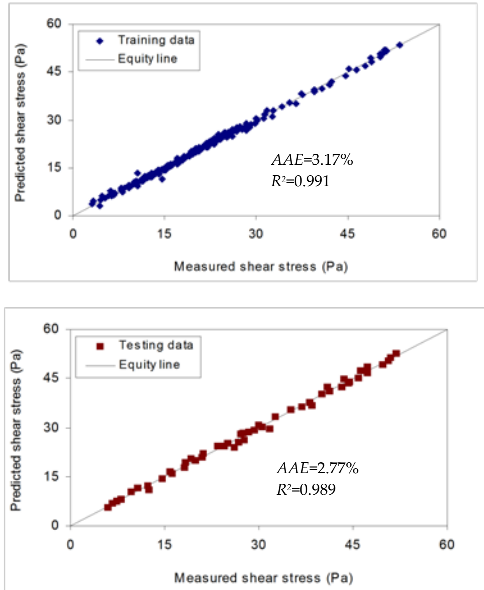


FIG. 9 MEASURED VERSUS ANN-MODEL PREDICTED SHEAR STRESS FOR OWC SLURRIES INCORPORATING PCM.

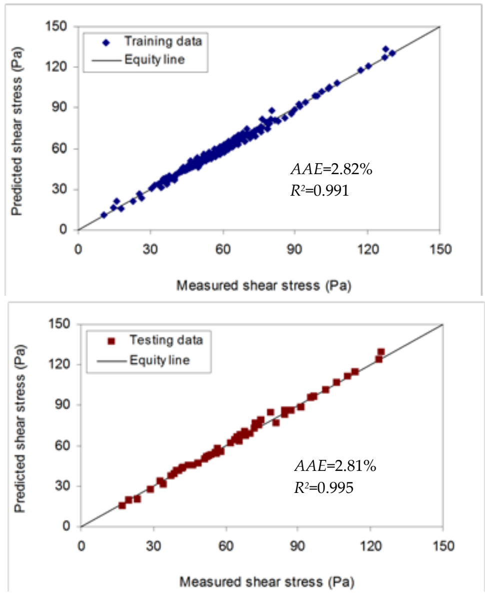


FIG. 10 MEASURED VERSUS ANN-MODEL PREDICTED SHEAR STRESS FOR OWC SLURRIES INCORPORATING LSM.

Figure 11 (a, b, c) represents the performance of models using the MRA technique in predicting the shear stress of OWC slurries incorporating PCH, PCM and LSM, respectively. All data points are

located on or in the vicinity of the equity line with an AAE of 4.83, 6.32 and 5.05% for slurries with PCH, PCM and LSM, respectively.

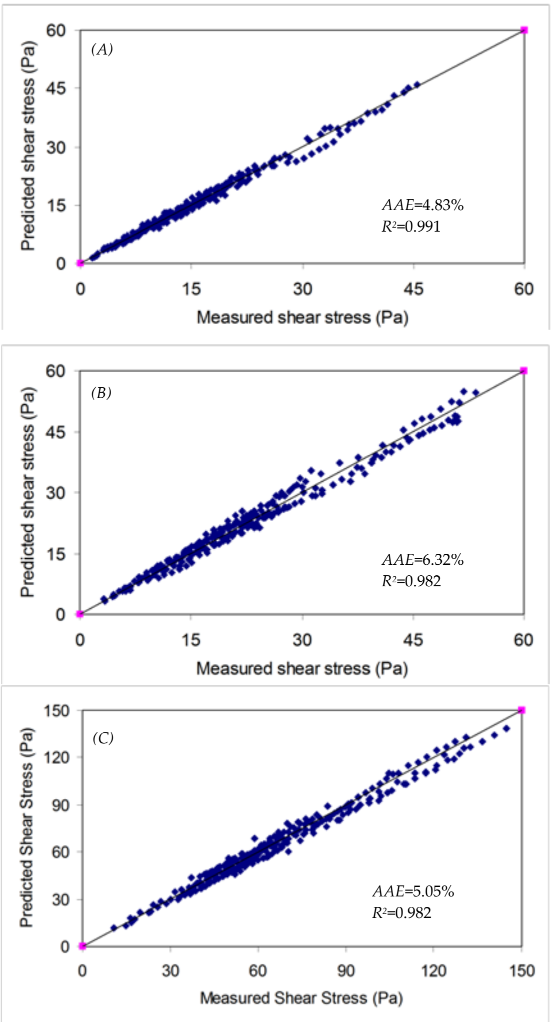


FIGURE 11 MEASURED VERSUS MRA–MODEL PREDICTED SHEAR STRESS FOR OWC SLURRIES INCORPORATING (A) PCH, (B) PCM, AND (C) LSM.

Table 3 reveals the relative importance of various parameters as well as their interactions in predicting the shear stress of OWC slurries prepared with PCH, PCM and LSM. It can be observed that the probabilities of the derived coefficients of all the parameters for PCH and PCM are limited to 3.9%. This implies that there is less than 3.9% chance, or 96.1% confidence limit, that the contribution of a given parameter to the tested response exceeds the value of the specified coefficient. In case of LSM, the probabilities of the derived coefficients of all the parameters are limited to 4.9%. Negative coefficients suggest that an increase of the given parameter results in a reduction of the measured response. Moreover, the value/coefficient of the parameter represents the importance of the given parameter on the response value. The higher the coefficient of the parameter, the greater is its influence. For example, an increase in temperature increases the shear stress for all the admixtures tested, and an increase in the dosage of the admixture reduces the shear stress in the case of PCH and PCM, but increases the response value in the case of LSM, which is in good agreement with the experimental results. Moreover, the admixture dosage was found to have more influence on the model response than that of the other parameters. The presence of interactions with coupled terms specifies that the influence of the parameter on a particular response is quadratic [Sonebi 2001].

The derived statistical models using the multiple regression analysis approach for shear stress of OWC slurries incorporating PCH, PCM and LSM have been selected based on the lowest average absolute error (AAE) and the highest correlation coefficient/determination coefficient (R2); they are given in Equations (5), (6) and (7), respectively.

$$\tau = 5.0 - 0.013\dot{\gamma} - 5.075D_A + 0.279T + 0.076\dot{\gamma}D_A + 0.001\dot{\gamma}T - 0.256D_AT - 0.002\dot{\gamma}D_AT \quad (5)$$

$$\tau = 5.0 - 0.022\dot{\gamma} - 8.849D_A + 0.429T + 0.085\dot{\gamma}D_A + 0.002\dot{\gamma}T - 0.220D_AT - 0.002\dot{\gamma}D_AT \quad (6)$$

$$\tau = 0.122\dot{\gamma} + 4.909D_A + 0.869T - 0.068\dot{\gamma}D_A - 0.072D_AT + 0.002\dot{\gamma}D_AT \quad (7)$$

The accuracy of the ANN- and MRA-based models thus developed was further evaluated by comparing the ratio of the measured-to-predicted values of the shear stress of OWC slurries. The maximum, minimum and average of the shear stress values, standard deviation (*SD*), and coefficient of variation (*COV*) and the average absolute error (*AAE*) for all the data are presented in Tables 4 and 5. The results reveal that both the ANN and MRA have successfully learned to map between input parameters (shear rate, dosage of respective admixture, temperature) and corresponding output (shear stress). The proposed models satisfactorily predicted the shear stress with acceptable error. However, the *AAE* of the models developed using the ANN approach was found to be lower than that of MRA-based models. The better performance of the ANN-based model was also supported by the higher correlation coefficient (R^2) than that provided by the MRA-based models.

7.2. Performance of ANN and MRA in Predicting Rheological Properties of OWC Slurries

Based on the satisfactory performance of the developed ANN and MRA models in predicting the shear stress of OWC slurries, the down flow curve for a particular mixture was predicted by changing the shear rate and keeping the admixture dosage and temperature unchanged. Subsequently, stress-shear rate curve corresponding to a zero shear rate, and the plastic viscosity was the slope of the curve. One slurry mixture for each of the admixtures was randomly selected from the testing data and used to develop the down flow curve at different temperatures (23°C, 45°C, and 60°C). These OWC mixtures were made with 0.5% of each admixture.

TABLE 3 MODEL PARAMETERS

	PCH (R^2 = 0.991)			PCM (R^2 = 0.982)			LSM (R^2 = 0.982)		
	Coeff.	*t*	*Prob.>|t|*	*Coeff.*	*t*	*Prob.>|t|*	*Coeff.*	*t*	*Prob.>|t|*
Intercept	5.000	-	-	5.000	-	-	0.000	-	-
$\bar{\gamma}$	-0.013	-2.076	0.039	-0.022	-3.439	0.001	0.122	7.514	< 0.0001
D_A	-5.075	-2.329	0.021	-8.849	-4.026	< 0.0001	4.909	1.723	0.086
T	0.279	10.323	< 0.0001	0.429	15.696	< 0.0001	0.869	12.275	< 0.0001
$\bar{\gamma} x D_A$	0.076	6.860	< 0.0001	0.085	7.633	< 0.0001	-0.068	-4.748	< 0.0001
$\bar{\gamma} x T$	0.001	7.765	< 0.0001	0.002	10.683	< 0.0001	0.000	-1.178	0.240
$D_A x T$	-0.265	-4.407	< 0.0001	-0.220	-3.619	0.000	-0.072	-0.919	0.359
$\bar{\gamma} x D_A x T$	-0.002	-7.329	< 0.0001	-0.002	-8.514	< 0.0001	0.002	5.030	< 0.0001

TABLE 4 PERFORMANCE OF ANN-BASED MODEL IN PREDICTING THE SHEAR STRESS OF CEMENT SLURRIES PREPARED WITH DIFFERENT CHEMICAL ADMIXTURES

Type of admixture	*AAE (%)*		$\tau_{measured}/\tau_{predicted}$					
			Average		*SD*[1]		*COV*[2] (%)	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing
PCH	3.43	2.76	0.984	0.988	0.058	0.040	5.88	4.09
PCM	3.17	2.77	0.998	1.001	0.062	0.040	6.18	4.01
LSM	2.82	2.81	1.000	1.000	0.042	0.041	4.23	4.11

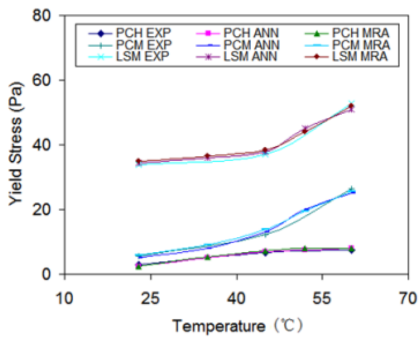
[1]SD: standard deviation, [2] $COV = SD / Average * 100$

TABLE 5 PERFORMANCE OF MRA-BASED MODEL IN PREDICTING THE SHEAR STRESS OF CEMENT SLURRIES PREPARED WITH DIFFERENT CHEMICAL ADMIXTURES

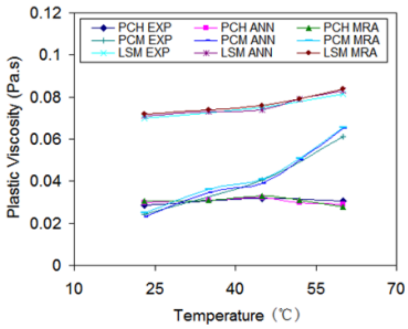
Type of admixture	*AAE (%)*	$\tau_{measured}/\tau_{predicted}$				
		Maximum	*Minimum*	*Average*	*SD*[1]	*COV*[2] (%)
PCH	4.83	1.165	0.805	1.006	0.062	6.128
PCM	6.32	1.203	0.864	0.999	0.073	7.348
LSM	5.05	1.167	0.854	1.018	0.059	5.804

[1]*SD*: standard deviation, [2] $COV = SD / Average * 100$

Figure 12 (a, b) represents the predicted yield stress and plastic viscosity values, respectively for OWC slurries incorporating 0.5% of PCH, PCM, and LSM at different temperatures, along with the corresponding experimentally measured values. Both the yield stress and plastic viscosity values predicted by the ANN- and MRA-based models followed a similar trend to that of the experimental data. In addition to test temperatures (23°C, 45°C and 60°C), rheological parameters were also determined at 35°C and 52°C in



(A)



(B)

FIG. 12 VARIATION OF (A) YIELD STRESS, AND (B) PLASTIC VISCOSITY OF OWC SLURRIES AT DIFFERENT TEMPERATURES (DOSAGE OF ADMIXTURE = 0.5% BWOC).

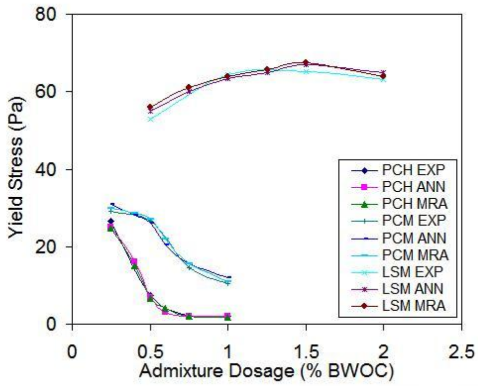
order to predict the model's response within the range of the input data.

It can be observed that the yield stress for OWC slurries incorporating PCH was generally lower than that for slurries made with PCM and LSM. This is in agreement with findings for cement pastes [Al-Martini and Nehdi 2007, Al-Martini 2008]. Both the yield stress and plastic viscosity were found to be sensitive to the change in temperature; the higher the temperature the higher was the yield stress, which is in good agreement with experimental results.

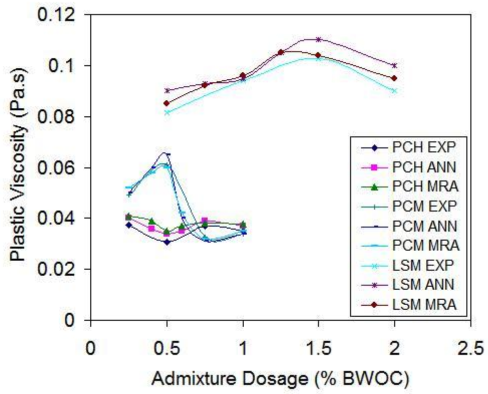
The effect of the admixture dosage at different temperatures on the predicted rheological parameters of OWC slurries is illustrated in Fig. 13. Some admixture dosages not used in experiments were also included in model predictions. Both experimental and predicted values of yield stress decreased with PCH and PCM dosage. In the case of LSM, the predicted yield stress values increased with the dosage up to 1.5% and then started to decrease, which is in good conformity with experimental results. It can be observed that the variation of yield stress with admixture dosage was reasonably estimated for all the admixtures considered and its predicted values were comparable to the corresponding measured data.

Moreover, the plastic viscosity of OWC slurries was found to be sensitive to the change of temperature and admixture dosage (Fig. 13(b)). The plastic viscosity values predicted by both the ANN- and MRA-based models showed irregular behaviour, which may be associated with the error involved in fitting the curve to the Bingham model. It was argued [Al-Martini and Nehdi 2007] that plastic viscosity measured by fitting the down flow curve of the hysteresis loop to the Bingham model does not always truly represent the material properties because of the error associated with fitting the curve, which could be sometimes high as observed by Saak [2000].

Figures 12 and 13 reveal that the models were able to recognize and evaluate the effects of the admixture dosage and temperature on yield stress and plastic viscosity. The *AAE* of the ANN model predictions was in the range of 1.4 to 15.6% and 0.7 to 11.8% for yield stress and plastic viscosity, respectively, and that for the MRA model was in the range of 1.2 to 17.5% and to 1.3 to 14.5% for yield stress and plastic viscosity, respectively; depending on the admixture dosage and temperature tested. The higher values of *AAE* are usually associated with the lower yield stress and plastic viscosity values since small prediction errors may result in high *AAE* in such cases.



(A)



(B)

FIG. 13 VARIATION OF (A) YIELD STRESS, AND (B) PLASTIC VISCOSITY OF OWC SLURRIES WITH ADMIXTURE DOSAGE AND AT A TEMPERATURE OF 60°C.

8. Concluding Remarks

In this study, the relationships amongst the shear stress, shear rate, temperature, admixture type and dosage for OWC slurries have been analyzed. The

rheological properties of OWC slurries were modeled using a feed-forward back-propagation artificial neural network and multiple regression analysis. The models were then used to develop flow curves, which were used to calculate the yield stress and plastic viscosity values for OWC slurries with different admixtures and at different test temperatures. Based on this study, the following conclusions can be drawn:

- The ANN model developed in this study was able to learn the relationships between different shear flow parameters for various OWC slurries and successfully predicted their rheological properties of slurries used in the training process. It also demonstrated satisfactory performance when input parameters (shear rate, temperature, and dosage of admixture) unfamiliar to the ANN were used. The results prove that the ANN model is a powerful tool to quantitatively predict the rheological properties of OWC slurries within the range of tested admixture dosages and test temperatures.
- The MRA-based models were able to predict the rheological properties of OWC slurries with adequate accuracy.
- The flow curves developed using the ANN- and MRA-based models allowed predicting the Bingham parameters (yield stress and plastic viscosity) of OWC slurries with an acceptable accuracy and were found to be in good agreement with experimental results.
- The models proposed by both approaches were found to be sensitive to the effects of temperature increase and admixture dosage on the rheological properties of OWC slurries.
- The ANN-based model performed relatively better than the MRA-based model in predicting the rheological properties of OWC slurries.
- The proposed ANN- and MRA-based models can be extended and used to limit the number of laboratory trial mixtures and develop OWC slurries with suitable rheological properties, thus saving time and reducing the cost of OWC slurry design for specific applications.

REFERENCES

Al-Martini, S., and Nehdi, M., "Effect of Chemical Admixtures on Rheology of Cement Pastes at High Temperature," Journal of ASTM International, Vol. 4, No. 3, 2007, 17 p.

Al-Martini, S., "Investigation on Rheology of Cement Paste and Concrete at High Temperature," PhD Thesis, The University of Western Ontario, 2008.

Al Martini, S, and Nehdi, M., "Coupled Effects of Time and High Temperature on Rheological Properties of Cement Pastes Incorporating Various Superplasticizers," ASCE Journal of Materials in Civil Engineering, Vol. 21, No. 8, 2009, pp. 392-401.

ANSI/API RP 10B-2, "Recommended Practice for Testing Well Cements," 1st Edition, July 2005, 171 p.

Bruni, C., Forcellese, A., Gabrielli, F., and Simoncini, M., "Modelling of the Rheological Behaviour of Aluminium Alloys in Multistep Hot Deformation Using the Multiple Regression Analysis and Artificial Neural Network Techniques," Journal of Material Processing Technology, Vol. 177, No. 1-3, 2006, pp. 323-326.

Cohen, J., Cohen, P., West, S. G., and Aiken, L. S., (2003). "Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences," 3rd Ed. Mahwah, NJ: Lawrence Erlbaum Associates, 2003, 736 p.

Demuth, H., Beale, M., and Hagan, M., "Neural Network Tool BoxTM 6 for Use with MATLAB R2008a," The Math Works Inc., Natick, Massachusetts, 2008, pp. 5.2 to 5.72.

El-Chabib, H., and Nehdi, M., "Neural Network Modelling of Properties of Cement-Based Materials Demystified," Advances in Cement Research, Vol. 17, No. 3, 2005, pp. 91-102.

El-Chabib, H., Nehdi, M., and Sonebi, M., "Artificial Intelligence Model for Flowable Concrete Mixtures Used in Underwater Construction and Repair," ACI Materials Journal, Vol. 100, No. 2, 2003, pp. 165-173.

Ferguson, J., and Kenblowski, Z., "Applied Fluid Rheology," Elsevier Applied Science, London and New York, 1991, pp. 209-210.

Genentech, "BioOncology Glossary," available online at http://www.gene.com/gene/news/kits/biooncology/oncologyterminology.html, accessed on July 13, 2010.

Guillot, D., "Rheology of Well Cement Slurries," Well Cementing, Edited by E.B. Nelson and Guillot, D. Schlumberger, Texas, 2006, pp. 93-142.

Health and Income Equity, Glossary, available online at http://depts.washington.edu/eqhlth/pages/academic_reso

urces/glossary.html#p, accessed on July 13, 2010.

Montgomery, D. C., Design and Analysis of Experiments, 7th Ed., Wiley, New York, 2009.

Ravi, K.M., and Sutton, D.L., "New Rheological Correlation for Cement Slurries as a Function of Temperature," SPE 20499, The 65th Annual Technical Conference and Exhibition of the Society of Petroleum Engineers, New Orleans, LA, Sept. 23-26, 1990, pp. 455-462.

Saak, W. A., Jennings, M. H., and Shah, P. S., "The influence of wall slip on yield stress and viscoelastic measurements of cement paste." Cement and Concrete Research, Vol. 31, n. 2, 2001, pp. 205–212.

Saak, W.A., "Characterization and Modeling of the Rheology of Cement Paste: With Application toward Self-Flowing Materials," Ph.D. Thesis, University of North Western, 2000.

Sonebi, M. "Factorial Design ModellingoOf Mix Proportion Parameters of Underwater Composite Cement Grouts," Cement and Concrete Research 31, No. 11, 2001, pp. 1553–1560.

Statsoft, Multiple Regression, Electronic Statistics Textbook, available online at http://www.statsoft. com/textbook /multiple-regression/, accessed on July 13, 2010.